ShuttleSpace: Exploring and Analyzing Movement Trajectory in Immersive Visualization

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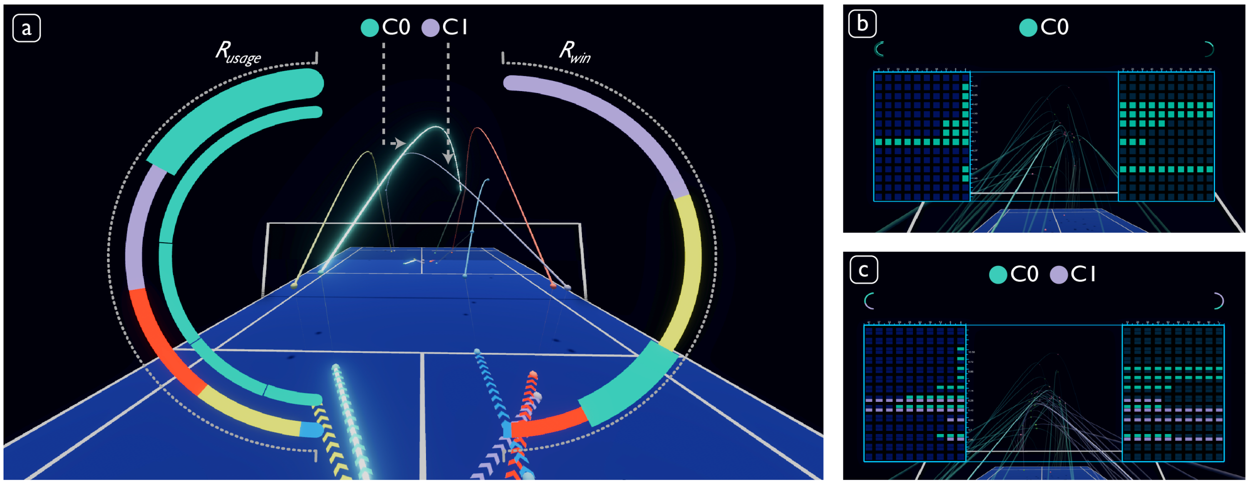

Fig. 1. ShuttleSpace is an immersive analytics system that allows a badminton coach to analyze the trajectory data from the player's perspective. a) The trajectories are visualized in a full-size simulated badminton court. Two semi-donut charts are displayed on the left and right side of the user's field-of-view (FOV) to present the usage and winning rates of the trajectories, respectively. b) Two grid-based visualizations show the distributions of usage and winning rates along the vertical positions. c) Comparing the usage and winning rates between two categories of trajectories.

Abstract—We present ShuttleSpace, an immersive analytics system to assist experts in analyzing trajectory data in badminton. Trajectories in sports, such as the movement of players and balls, contain rich information on player behavior and thus have been widely analyzed by coaches and analysts to improve the players' performance. However, existing visual analytics systems often present the trajectories in court diagrams that are abstractions of reality, thereby causing difficulty for the experts to imagine the situation on the court and understand why the player acted in a certain way. With recent developments in immersive technologies, such as virtual reality (VR), experts gradually have the opportunity to see, feel, explore, and understand these 3D trajectories from the player's perspective. Yet, few research has studied how to support immersive analysis of sports data from such a perspective. Specific challenges are rooted in data presentation (*e.g.*, how to seamlessly combine 2D and 3D visualizations) and interaction (*e.g.*, how to naturally interact with data without keyboard and mouse) in VR. To address these challenges, we have worked closely with domain experts who have worked for a top national badminton team to design ShuttleSpace. Our system leverages 1) the peripheral vision to combine the 2D and 3D visualizations and 2) the VR controller to support natural interactions via a stroke metaphor. We demonstrate the effectiveness of ShuttleSpace through three case studies conducted by the experts with useful insights. We further conduct interviews with the experts whose feedback confirms that our first-person immersive analytics system is suitable and useful for analyzing badminton data.

Index Terms—Movement trajectory, badminton analytics, virtual reality

1 Introduction

Trajectory analysis is a key concern in sports data science; thus, it has been widely studied in soccer [2,33], tennis [30], table tennis [45], and badminton [36]. In badminton, coaches often analyze the trajectories of shuttles or players from a 3D perspective, as the heights of the flying shuttle and the player's movement are non-negligible factors for the success of a rally. Prior research [6,42] on trajectory analysis for badminton mainly develops dimensionality reduction and view coordination methods to visualize the 3D information on a 2D screen, thereby leading to a cognitive load of the analyst who has to mentally reconstruct the 3D scenario. Furthermore, these systems usually display the data in court diagrams, which is an abstraction of reality, causing experts to face difficulty in imagining the situation on the court and understanding why the players behaved in a certain manner.

Recent advances in immersive technology, especially VR, have shed new light on 3D trajectory analysis. Existing research [8,24,38,47] has repeatedly reported that VR offers benefits such as increased spatial understanding, rich semantic interaction, peripheral awareness, and large information bandwidth. In badminton, VR provides two unique benefits that traditional desktop platforms cannot provide: 1) the ability to present the 3D representation in a "real 3D" form, which is particularly suitable for visualizing 3D trajectory data; and 2) the capability to

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simulate the real court in an immersive environment, which allows the analysts to see and feel the 3D trajectories from the player's perspective. Considering these benefits, we aim to design a VR-based interactive analysis system to assist badminton coaches in analyzing trajectories.

We worked closely with four domain experts to develop such an immersive analytics system. Our domain experts include badminton coaches and data analysts who have worked for a top national badminton team in the world over 5 years. During the collaboration, we came across two major challenges. First, it is difficult to **seamlessly visualize the 3D trajectory data together with 2D statistical information** (*e.g.*, usage rate) **from a player's perspective**. Experts typically analyze both the 3D trajectory data and 2D statistical information. In particular, the experts would like to perceive the data from the player's perspective, which allows perceiving the kinematic features effectively (*e.g.*, the highest point of trajectories, the distance between the placement and the player's position) by leveraging the proprioception and spatial awareness. However, careful design is necessary to visually combine 3D and 2D data without hindering the perceptual effectiveness, such as occlusion and distortion. Though prior work [9] investigates the ways to combine 3D and 2D visualizations in immersive environments, only few methods have been proposed to achieve this combination from a first-person view. Second, **an efficient and natural approach for badminton trajectory selection in VR is absent.** When exploring the trajectories, analysts have to frequently interact with various trajectory partitions to perform in-depth analysis. However, selecting trajectories, a type of 3D curve data, in VR environments is tedious and demanding. Most of the existing methods, such as bi-manual interaction [15] and elaborate gesture [14], are designed for 3D line data that can be moved and rotated; thus, they are not suitable for our scenario where the trajectories are fixed in a simulated court.

To address these challenges, we propose ShuttleSpace, an immersive system that enables coaches to analyze badminton strokes through interactively exploring the trajectories from a player's perspective. To address the first challenge, we design a first-person perspective visualization that leverages the peripheral vision to seamlessly blend the 3D trajectory data with 2D statistical information. Peripheral vision [41] is the vision that occurs outside the center of gaze (*i.e.*, 10°). Different from traditional desktop platforms that usually display the data within the center of gaze, VR devices allow us to display the data in a wide field-of-view (FOV). Thus, we adopt a focus+context diagram to visualize the 2D statistical information in the near-peripheral (*i.e.*, 15°-30°) vision as the context for the 3D trajectory data. For the interaction challenge, we exploit the VR controller and design a stroke metaphor that enables the analysts to select trajectories by swinging the controller to imitate stroking a shuttle. We achieve this by developing a machine learning-based model that queries trajectories based on the user's action. Such a selection method is natural for badminton experts and allows them to efficiently interact with 3D trajectories in VR without using keyboard and mouse. To demonstrate the usefulness of ShuttleSpace, we present three case studies conducted by the domain experts on a real-world dataset. We further report the experts' feedback gathered from the post-study interviews.

Our primary contribution is the design and implementation of ShuttleSpace. The system features 1) a novel first-person perspective visual design that seamlessly combines 2D and 3D visualizations and 2) a metaphorical interaction to select trajectories efficiently and naturally. We evaluate our system by presenting three case studies on real-world datasets conducted by four domain experts. We also summarize the experts' feedback on using the immersive system to analyze badminton data.

2 Related Work

Visualization for Sport Trajectory. Sports trajectory data has been widely studied. Researchers have developed various visual analytics systems for trajectory data in different sports such as tennis [11, 30, 31], baseball [19, 28], and soccer [40]. These systems can be roughly divided into two categories: visualizing trajectories in 2D and 3D.

Typically, 2D visualization techniques present the trajectories from a top down view, allowing the analysts to investigate the movements of the players on the ground [45, 46]. To reduce the visual clutter of large-scale trajectories, researchers have utilized aggregation methods, such as convex hulls [2] and K-means clustering [33], to group the trajectories into clusters. Besides the trajectory data, many systems provide additional details by using focus+context techniques. Sacha et al. [34] designed and proposed a court overview accompanied by custom views to assist the analysts in identifying meaningful events. SoccerStories [27] visualizes important trajectories in each soccer phrase with extra information to facilitate the exploration. To capture features related to the trajectory, Forvizor [46] detects formations from players' position and presents the formation evolution through a narrative timeline representation. Although these 2D methods demonstrate effectiveness in analyzing the player trajectories, they cannot be directly adapted to the ball trajectories whose height does matter. On the other hand, several visualization systems have been proposed to support analyzing the trajectories of balls in 3D space. For example, LucentVision [29] provides 3D virtual replays of the ball trajectories to help analysts exam the quality of serves. Baseball4D [12] reconstructs and presents the 3D trajectories of balls using a heatmap to support analyzing the relationships between hits and ball drops in baseball games. Chen et al. [7] approximated 3D volleyball trajectories from video frames and then classified them to infer the tactical information.

All of these systems, however, are designed for traditional desktop platforms; thus, they do not fully leverage the benefits of VR environments, such as stereoscopic 3D and reality simulation. In this work, we design a VR system to support immersive analytics of badminton data.

First-person-oriented Sports Applications in VR. A first-person-oriented sports application allows the user to see, explore, and experience the data and situation from a player's perspective [4]. Given the emergency of VR techniques, this method has been increasingly used over the last several years [18, 37, 43, 44]. For instance, to improve the player's ability to estimate the position of other players, Shimizu and Sumi [37] developed a head-mounted display (HMD) VR system that simulates ball games from a first-person view and allows the user to rearrange all players. The user can then perform actions specific to the ball game such as passing and receiving a ball. Besides HMD, additional devices and equipment have been used to simulate reality. Nozawa et al. [26] proposed a VR ski training system in which the user can ski on an indoor ski simulator and follow a virtual coach through an HMD. HeatSense [32], a thermal sensory supplementation system for superhuman sports, provides hot and cold experience for the user in the VR based on the thermal and vibrotactile feedback.

However, these first-person perspective VR applications mainly focus on reproducing the scenario and experiences rather than visualizing data to support visual analysis. Rarely has research explored how to enable a first-person-oriented analysis of sports data in VR. We systematically study this issue and propose a first-person perspective immersive analytics system that features novel visual design and interaction for 3D and 2D sports data.

Selection Techniques for Immersive Visualization. Selection is a fundamental task in exploratory analysis because it is a prerequisite for many other subsequent interactions [3]. Although researchers have explored the selection of 3D visualizations on traditional desktop platforms, such as 3D point-based selection [10], only a few studies have been conducted on the selection techniques specific for immersive visualization. Prior work has introduced selections for abstract and spatial data. Huang et al. [14] designed dedicated gestures to allow users to select nodes and edges in immersive graph visualizations using bare hands. However, the system is limited by the low accuracy of recognizing gestures. Instead, VRRRRoom [39] combines VR HMDs with touch input surfaces to support the analysis of medical images. In the system, the user can interact with the volume visualization through gestures on a desktop surface. The gesture recognition is accurate due to the touch input surface. Other than gestures, Hurter et al. [15] proposed FiberClay, a system that utilizes VR controllers to enable 6 degree-of-freedom (DOF) selection of 3D trajectories in VR environments. In FiberClay, the user can progressively filter trajectories through bi-manual brushing while easily navigating to different viewpoints, *e.g.*, rotating and scaling the trajectories.

Inspired by FiberClay, we also utilize VR controllers to support accurate 6 DOF interactions of 3D trajectories. However, the power of FiberClay will be weakened in our scenario, since the simulated court and the trajectories cannot be moved, rotated, and scaled. We address such issues with a novel metaphorical approach that allows the user to select shuttle trajectories by swinging the VR controller, which mimics swinging a racket.

3 Background and Design Requirements

In this section, we introduce the background and data of badminton analysis, followed by the requirement analysis and system workflow.

3.1 Background

Badminton is a sport that opposes two or four players in a rectangular court divided into two equal halves by a net. Two players, one on each side, hit a shuttle with a racket and aim to land the shuttle within the opponent's half-court. A formal badminton match consists of a best-of-three series in which the first player who wins two games wins the series. To win a game, a player needs to win 21 rallies. Specifically,

- A **rally** is the process of scoring one point, which starts from a serve (*i.e.*, the first shot), ends with the score of one side, and usually contains a series of shots between the opposing players. To win a rally, the player has to perform high-quality strokes that limit the opponent's performance.
- A **stroke** is the swing motion of an arm to complete a shot. The process of a stroke usually involves three stages: 1) a player moves to a hit position, 2) the player strokes the shuttle that flies towards the opponent's half-court, and 3) the opponent moves to return the shuttle. To perform a high-quality stroke, a player usually uses different techniques based on the specific situation.
- A **technique** is a method to perform a stroke, such as *lob*, *net shot* or *smash*. A technique can further be divided into subtypes, such as *defensive lob* and *offensive lob*. Different techniques result in different speed and trajectories of a shuttle. A player should improve his/her skills and understanding of techniques to perform high-quality strokes.

In summary, a stroke is the minimal "tactical unit" for winning a badminton game. Thus, coaches are particularly interested in and pay attention to the analysis of players' strokes. Coaches usually collect the data records of strokes in a badminton match.

3.2 Data Description

Table 1. Main attributes of a stroke record.

Trajectory Data		
T^1_{player}	Player trajectory	The trajectory of the player who moves to perform the stroke, which is defined by its start end end positions $\{P_{start}, P_{end}\}$.
T^2_{player}	Player trajectory	The opponent's trajectory to return the shuttle, which is also defined by its start end end positions $\{P_{start}, P_{end}\}$.
$T_{shuttle}$	Shuttle trajectory	The 3D trajectory of the shuttle, defined by its start, highest, and end position $\{P_{start}, P_{highest}, P_{end}\}$.
Statistical Data		
R_{usage}	Usage rate	The usage frequency of the technique used in this stroke.
R_{win}	Winning rate	The winning frequency of the technique used in this stroke.

The main attributes of a stroke record can be divided into two parts, namely, trajectory data and statistical data (Table 1):

- **Trajectory data** is a kind of physical data, including two player trajectories T_{player} (one for each player) and one shuttle trajectory $T_{shuttle}$. A player trajectory is recorded as two points, *i.e.*, $T_{player} = \{P_{start}, P_{end}\}$, while a shuttle trajectory is recorded as three points, *i.e.*, $T_{shuttle} = \{P_{start}, P_{highest}, P_{end}\}$. Each point is represented by its 3D position (x, y, z) and velocity (v_x, v_y, v_z). We call the positions of these points ***kinematic features*** of a trajectory. In this work, these key points are extracted from match videos [35]. We then reconstruct $T_{shuttle}$ based on the key points with a high-accuracy aerodynamic model [36]. The model considers several factors including gravity, air drag force, and the shape of the shuttle, and allows us to calculate the 3D position of a shuttle with respect to time. As for T_{player}, we assume that the players moved in straight lines.
- **Statistical data** is a kind of abstract data that has no predefined spatialization, including the winning rate R_{win} and usage rate R_{usage} of the technique used in this stroke.

A stroke record also includes the used technique, the outcome (*i.e.*, win, lose, or continue), and a pointer to its previous stroke.

3.3 Requirement Analysis

To understand how coaches and analysts work on badminton data, we held two-hour weekly meetings with four domain experts over one year. One of the experts is a badminton professor who works for a top national badminton team. The other three experts are postgraduate students of physical education with a focus on badminton. They are proficient in badminton and have rich experiences in badminton training.

During the requirement analysis, we actively communicated with the experts, demonstrated several prototype systems (*e.g.*, desktop-based and VR-based) to them, and collected feedback to refine our design goals. After several rounds of iterations, we summarize the requirements from the experts and conceive five design goals:

G1 Visualizing the data from the player's perspective. *What does the situation look like from the player's perspective? How far and fast should the player run to return the shuttle?* The experts are particularly interested in understanding the situations of a stroke from the player's perspective. They expect to embed the data on the court so that they can see and feel the situation straightforwardly rather than imagining the scene. Therefore, a first-person perspective design that simulates the real court and presents the data in a player-centred manner should be adopted.

G2 Allowing multi-granularity analysis of trajectory data. *Are there any patterns in the strokes? What kinds of strokes are most frequently used by players? What are the usage/winning rates of these strokes?* To answer these questions, experts often cluster strokes into categories, examine different categories to identify the patterns of good strokes and finally analyze the individual strokes. Therefore, the system should allow multi-granularity analysis, *i.e.*, support grouping strokes into categories and unfolding a category for investigating individual strokes.

G3 Supporting visual correlation analysis. *How is the outcome of a stroke affected by the kinematic features? How is the outcome affected by the techniques used in the previous or next stroke?* When probing into a specific category of strokes, the experts aim to understand the relationship between kinematic features and the usage/winning rate. Furthermore, the relationship between the stroke outcome and techniques used in the previous stroke is an important factor to develop a winning strategy. Thus, the system should support such correlation analysis.

G4 Providing natural interactions for searching strokes. *What are the usage and winning rates of strokes like this?* An expert typically queries a specific part of the strokes. However, the searching conditions can be complex and indescribable, *e.g.*, the strokes of swinging the arm in a certain direction at a certain speed. To this end, natural interactions should be provided to enable the searching of strokes.

G5 Revealing the differences between strokes for comparison. *What are the differences between two strokes?* A comparison is a necessary function that can help experts gain insights. Aside from analyzing the different strokes of a player, analyzing the strokes between two players is particularly useful to develop a winning strategy. Thus, the system should provide effective methods for comparative analysis.

3.4 System Workflow

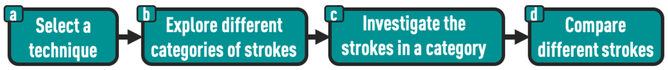


Fig. 2. System workflow for stroke analysis.

Figure 2 shows the analysis workflow of our system. First (Fig. 2a), the user chooses the strokes of a specific technique (*e.g.*, lob, smash) as the study target. Then (Fig. 2b), our system classifies the strokes into multiple categories based on their trajectories using HDBSCAN [25]. The user can observe the visual summary of different categories and select a category by using natural interactions for further investigation. After choosing a category (Fig. 2c), our system allows the user to explore the relationships between trajectory and statistical data. Finally (Fig. 2d), the user can select a different subset of data for comparisons.

4 SHUTTLESPACE

In this section, we present ShuttleSpace, a stroke analysis system that incorporates the five design requirements. We first use a usage scenario to demonstrate the workflow and then introduce the three key components, *i.e.*, trajectory data visualization, statistical data visualization, and natural interactions.

4.1 Usage Scenario

Samwell is a coach of a university badminton team. To prepare for the next match of Jon, the best player of his team, Samwell needs to analyze Jon's lob strokes as it is used most frequently by Jon.

Samwell loads Jon's stroke data into ShuttleSpace and chooses *lob* strokes as the study target, following the system workflow in Fig. 2. After wearing the HMD, Samwell is immersed in a full-size badminton court simulated by the VR system. Samwell appreciates this simulated court because it allows him to perceive the data from Jon's perspective (G1). Each stroke is visualized as one shuttle trajectory and two players' trajectory. ShuttleSpace automatically groups these trajectories into five categories (Fig. 1a) (G2). For each category, the system aggregates the trajectories within and shows an average trajectory as the visual summary. Different categories have different colors. Two semi-donut charts are displayed on the left and right sides of Samwell's FOV, presenting the R_{usage} and R_{win} of different categories (G3).

Samwell is interested in the green category (*i.e.*, `C0`) because it has the highest R_{usage} but a low R_{win} (Fig. 1a). He selects this category by swinging the VR controller to imitate stroking a shuttle (G4). ShuttleSpace then enters a detail view (Fig. 1b) and unfolds the trajectories in this category. Samwell wants to check the relationships between the R_{usage} or R_{win} and the height of $P_{highest}$. He opens *Grid View* that presents the distributions of R_{usage} and R_{win} along the height of $P_{highest}$ (G3) using two grid-based visualizations (Fig. 1b). He discovers that most of the trajectories with a middle $P_{highest}$ have a high R_{usage} but a low R_{win} while those with a high or low $P_{highest}$ have a high R_{win}.

Finally, Samwell further compares (G5) `C0` with another category (*i.e.*, `C1`) that has a high R_{win}. The comparison in *Grid View* (Fig. 1c) confirms that trajectories with a low $P_{highest}$ tend to have a high R_{win}.

4.2 Visual Design for Trajectory Data

We leverage VR to fulfill the design goal that has the highest priority (G1), as VR offers the ability to simulate the reality, allowing the expert to view and feel the data and situation from the player's perspective. Specifically, in ShuttleSpace, we simulate a full-size (*i.e.*, $6.1 \times 13.4m^2$) badminton court (Fig. 3), where the trajectory data is presented.

Visualization of a single stroke. According to Table 1, a stroke is visualized as three trajectories, namely, a ballistic trajectory for the shuttle ($T_{shuttle}$ in Fig. 3) and two arrow trajectories for the two players

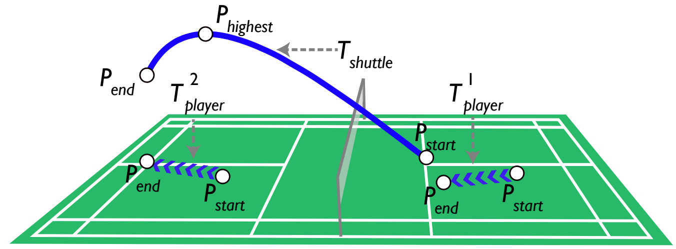


Fig. 3. A visualization of the trajectory data of a stroke, including three trajectories: one shuttle trajectory in the air and two player trajectories on the ground. The arrows indicate the movement direction of the players.

(T^1_{player} and T^2_{player} in Fig. 3). These trajectories present the complete process of a stroke: from one player moving to shoot the shuttle to his/her opponent being ready to return it. To facilitate the analysis, we highlight the key points in the trajectories, that is, $\{P_{start}, P_{highest}, P_{end}\}$ in the $T_{shuttle}$ and $\{P_{start}, P_{end}\}$ in a T_{player}. By observing these trajectories, experts can effectively judge the situation on the court and assess the quality of the stroke. For example, the expert can stand at the opponent's position to see the $P_{highest}$ of the coming shuttle and easily justify whether the shuttle will be intercepted by a powerful smash or cause a passive return.

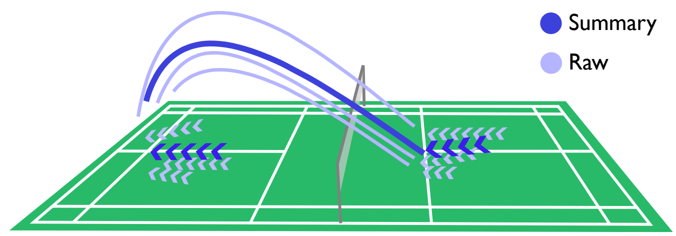


Fig. 4. A visual summary of multiple strokes in a category. In overview mode, the raw trajectories are aggregated to show a trajectory (in dark purple). In a detail mode, the average trajectory is unfolded to the raw trajectories (in light purple).

Visual summary of multiple strokes. A visual summary of the trajectory data is necessary (G2) due to the existence of thousands of strokes in a badminton match, and visualizing them all leads to severe visual clutter. Thus, we use a hierarchical DBSCAN (HDBSCAN) [25] to group the trajectory data into several categories. We select HDBSCAN because it is a non-parametric algorithm that enables us to achieve the clustering results without specifying the cluster numbers.

We use three steps to cluster the trajectories: 1) after reconstructing the trajectories (two T_{player} and one $T_{shuttle}$) of a stroke based on the seven key points, we sample the points on the trajectories by using equidistant sampling (*i.e.*, every 10cm); 2) next, we import the sampled points of all trajectories into HDBSCAN to obtain the point clusters; 3) for each trajectory, we count its points and assign the cluster with the most number of points to it as its category. There is only one primary parameter in HDBSCAN, namely, minimum cluster size. In our study, we empirically set it to 50. The quality of the clustering method was assessed by our domain experts (using a dataset different from the one used in the case studies) during the collaboration.

To visualize a category, we aggregate the trajectories within the category and visualize the aggregated trajectory in the same manner as a single stroke. Specifically, we average the corresponding key points of the trajectories within a category and then construct three representative trajectories (*i.e.*, two T_{player} and on T_{player}) based on these averaged key points. The representative T_{player} and T_{player} are presented as the visual summary of the category. Different categories are encoded in different colors. As shown in Fig. 4, the summary trajectory provides a concise representation of multiple strokes. We visualize a category in this manner to include two considerations: 1) reduce the visual clutter and 2) keep the information of key points as much as possible. An aggregated trajectory is a simplification and estimation of the category but preserves the averaged key points of the category, providing the representative information for the expert. When performing in-depth investigations, the expert can select a category to unfold it into the raw strokes (Fig. 4) by using natural interactions introduced in Sec. 4.4.

Visual comparison of trajectory data. Supporting visual comparison of trajectory data (G5) in ShuttleSpace is natural. We can visualize the trajectories in the simulated court for a comparison.

4.3 Visual Design for Statistical Data

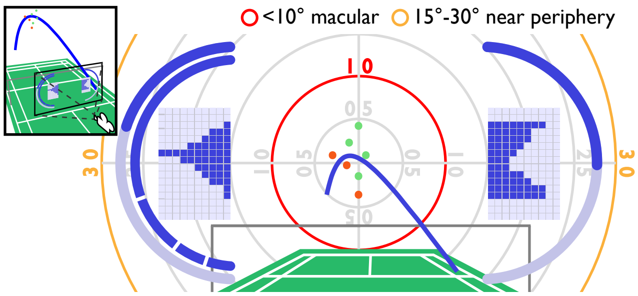


Fig. 5. Visualizing the statistical data by leveraging the wide FOV of VR HMD. The 3D trajectories are naturally displayed at the center of the gaze (*i.e.*, 10°). The statistical data is shown in the near-peripheral (*i.e.*, 15° to 30°) by using semi-donut charts and grid-based visualizations. In practice, we zoom out the semi-donut charts to small icons while the grid-based charts appear to simplify visual elements in the peripheral region. The figure at upper-left shows the position of statistical data display and the 3D trajectories.

The experts intend to explore the relationships between trajectory and statistical data (G3). Different from trajectory data, which is a type of physical data with inherent 3D representations, the statistical data (*i.e.*, winning rate R_{win} and usage rate R_{usage}) is a type of abstract data that has no pre-defined spatialization, and thus are preferred to be displayed in a 2D form. Considering the context of a first-person perspective, we design *Donut View* and *Grid View* to reveal the relationships between trajectory and statistical data on different levels (Fig. 5).

***Donut View*—overview level.** We use *Donut View* (Fig. 6) as it naturally presents R_{usage} and R_{win} of strokes in different categories [5]. *Donut View* consists of a left and a right semi-donut charts that present R_{usage} and R_{win}, respectively. The usage of techniques used in previous or next strokes are presented by a smaller semi-donut chart at left. We place *Donut View* in the screen space instead of world space. Thus, *Donut View* follows the user's movement and always appear within the user's FOV. *Donut View* adopts a focus+context paradigm that presents the statistical data as the context of the trajectory data. Therefore, the presented data in *Donut View* is dynamic updated according to the trajectories within the user's FOV, which means that only the R_{usage} and R_{win} of the trajectories seen by the user will be presented. The sectors in *Donut View* are displayed in descending order. We use colors to relate the sectors to the categories of trajectory. The user can further select a sector to check the R_{usage} distribution of techniques used in its previous or next strokes. Through *Donut View*, the users can naturally perceive the trajectory and statistical data.

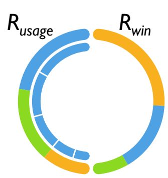
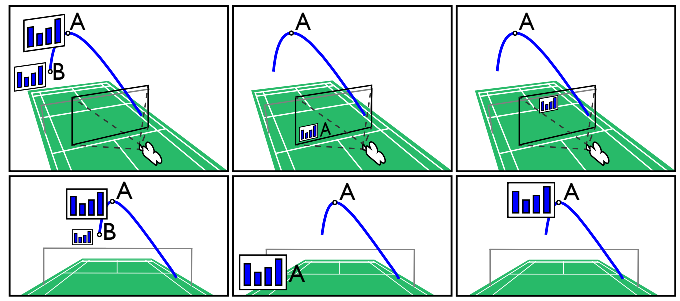


Fig. 6. *Donut View*

The design of *Donut View* mainly incorporates three considerations: the visual design should always be 1) **legible** to the user wherever he is in the simulated court, 2) **occlusion-free** with regard to the trajectories, and 3) with **high-bandwidth** by leveraging the wide FOV of VR as much as possible. To fulfill the legibility, we place *Donut View* in the screen space instead of the world space. For the other two considerations, we propose to leverage the *peripheral vision* [16, 17]. Peripheral vision occurs outside the center of gaze (Fig. 5) and allows perceiving information in parallel with the central vision. Different from traditional desktop platforms that mainly present information within the macular, *i.e.*, 10°, VR HMD allows us to display information in a wider visual field, *i.e.*, 55°. A key observation is that the trajectories are usually located within the macular when the user observes them. Thus, we can display the extra data in the peripheral vision to extend the information bandwidth without occluding the trajectories. Considering the characteristics of human vision system [41], we visualize the statistical data in the near-peripheral (*i.e.*, 15° to 30°) with a semi-donut shape so that the user can read the visualization effortlessly. By this, we seamlessly combine the 2D and 3D visualizations. Figure 7 presents several alternative designs but all of them cannot satisfy our three considerations.



(a) world space (b) screen space: corner (c) screen space: region

Fig. 7. Three design alternatives for *Donut View*. The first row shows the court and charts from a third-person perspective. The camera indicates the user's position and the black frame indicates the user's screen space. The second row shows the scenes from a first-person perspective. a) Display the charts as 3D objects in the 3D world space. b) Fix the charts at the corner of the 2D screen space. c) Place the charts in the screen space, close to the target.

***Grid View*—detail level.** When examining the details of strokes in a category, we present *Grid View* (Fig. 8) to reveal the relationships between R_{usage} or R_{win} and the trajectory data (G3). Specifically, the experts expect to explore how the kinematic features of a trajectory (*i.e.*, the position of P_{start}, P_{end}, and $P_{highest}$) affect R_{usage} and R_{win}.

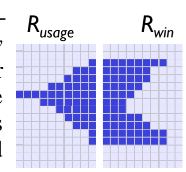


Fig. 8. *Grid View*

For the $T_{shuttle}$, the experts are mainly interested in the vertical position of the three key points. Figure 5 presents an example of analyzing the vertical positions of $P_{highest}$. We use two grid-based visualizations on the left and right side of these $P_{highest}$ to visualize the distributions of R_{usage} and R_{win} along the vertical positions, following the same convention in *Donut View*, *i.e.*, the left for R_{usage} and right for R_{win}. The colors of these grids also represent the categories of the strokes.

For the T_{player}, the experts focus on the distances between P_{start} and P_{end}. Thus, we design a variation of *Grid View* (Fig. 9). Specifically, we display a polar coordinate on the ground, which is centered at the aggregated P_{start}, (*i.e.*, the P_{start} of the aggregated T_{player} of this category). The direction of the coordinate follows the FOV of the user. Two grid-based visualizations are attached on the left and right side, presenting the R_{usage} and R_{win} distributions along the distance between P_{start} and P_{end} when user stands at the aggregated P_{start} and uses it as a reference point.

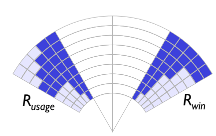


Fig. 9. Variation of *Grid View*

One main purpose of *Grid View* is to help experts discover outlier patterns, including the strokes with 1) high R_{usage} but low R_{win} and 2) low R_{usage} but high R_{win}. From *Grid View*, the user can easily identify these patterns by observing which direction the grids in one row lean to. For example, if the grids in one row lean to the left (*e.g.*, Fig. 5), then the strokes whose $P_{highest}$ passes this vertical position are used frequently (high R_{usage}) but score less (low R_{win}); on the other hand, low R_{usage} but high R_{win} occur if the grids lean to the right.

Visual comparison of statistical data. We reuse the design of *Donut View* and *Grid View* to support comparisons of statistical data (G5).

Specifically, when the user wants to compare R_{usage} and R_{win} of two trajectories in an overview level, we present them in *Donut View* (Fig. 12b), where the color of a sector represents the trajectory it denotes. To compare R_{usage} and R_{win} at a detail level, we use a grouped grid-based design in *Grid View* (Fig. 12c), where each row is divided into two sub-rows, each presenting the data of one trajectory. The color of a grid also denotes the trajectory it refers to.

4.4 Natural Interaction

Experts require efficient and effective interactions to select trajectories in VR for interactive exploration (G4). To achieve this goal, we propose that the interaction should be: 1) **intuitive** such that it comes naturally without conscious reasoning for the expert, 2) **feasible** such that it can be easily performed by the expert, and 3) **expressive** such that it is sufficient for the expert to select the trajectories he wants. Considering these three issues, we design *VirtualStroke*, a novel metaphorical interaction that allows the user to select trajectories by waving the controller in a way similar to stroking. This is achieved by a trajectory simulation with a speed correction based on the user's motion.

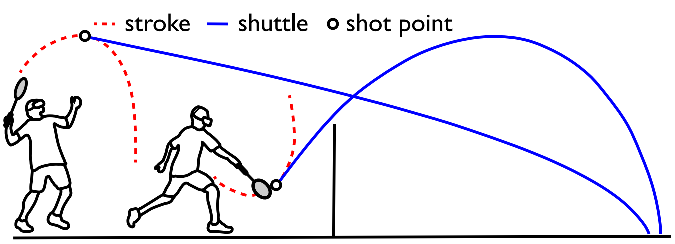


Fig. 10. Using *VirtualStroke* to select trajectories. The user sets a shot point and uses the controller as a racket to perform a stroke action. The target trajectories are selected based on the simulation of the stroke.

Metaphorical interaction design. In practice, a shuttle trajectory is determined by the stroke. A player with a certain badminton skill can easily control the shuttle trajectory by adjusting the direction, speed, and position of the stroke. It is also very familiar to our domain experts that use strokes to specify trajectories. Thus, we design *VirtualStroke* that leverages the VR controller to allow the expert to select trajectories through strokes. Specifically, as shown in Fig. 10, to select a subset of trajectories, the expert moves to a shot region, specifies a hit point, and holds the controller as a racket to perform a stroke. By this means, we obtain the hit position and velocity. With these parameters, ShuttleSpace then selects the target trajectories in two steps: 1) simulating a virtual shuttle trajectory based on the aerodynamic model and then 2) querying shuttle trajectories whose three key points (*i.e.*, P_{start}, $P_{highest}$, and P_{end}) are all within $1m$ (a predefined threshold) of those of the simulated trajectory. This metaphorical interaction fulfills all our three design considerations and has many benefits, such as 1) the VR controller provides the affordance to be held as a racket; 2) the learning curve is gentle for the experts as they are familiar with stroke actions; and 3) compared with the keyboard and mouse, the interaction is expressive to specify trajectories. In addition to *VirtualStroke*, ShuttleSpace also supports other common interactions on the VR platform, such as click and touch through the controller, as well as gaze-based interactions supported by the HMD.

Neural network for speed correction. A critical input parameter of our selection is the hit velocity, which is controlled by waving the VR controller. However, our experts can hardly swing the controller (which is quite different from a real racket) as fast as top players. Thus, to mitigate this mismatch, we use a neural network to correct the stroke speed of the controller. Specifically, we use a standard three-layer perceptron to map the stroke speed of the controller to the one of a real racket. We choose 1 neutron for the output layer and 16 for the others to strike a balance between robustness and efficiency for the scalability of our problem—mapping a scalar value to another. A Mean Absolute Error (MAE) loss function is adopted.

Dataset and Performance. We follow a typical machine learning pipeline to build up our mapping model [23]. To train the model, we collected a dataset with over 500 stroke records from a group of participants, including five experienced amateurs and the five domain experts collaborated with us. Specifically, we asked the participants to perform strokes according to the displayed shuttle trajectories. For each given trajectory, we asked the participants to repeat the stroke three times. In total we collected 350 and 150 records from the domain experts and experienced amateurs, respectively. Then we used the stroke speed as the input and the real stroke speed as the ground truth. Overall, the records are of high quality and collected from participants with similar skill levels of the target user of ShuttleSpace. Therefore, the dataset will not introduce a biased model. Figure 11a presents the MAE per epoch for the training and testing sets in the training process. We notice that the MAE of the training set decreases smoothly, while the one of the testing set decreases with a small gap to the training MAE. This observation reveals that our model does not suffer from the overfitting problem [13].

We evaluated the model by assessing its time performance and accuracy. To evaluate the time performance, we counted the calculation time for a stroke record from model input to output and repeated this process for 500 times on a computer equipped with a CPU. The average calculation time for a stroke record is $187ms$. Since our model structure is not complex, the computation is fast enough to support interactions. The computation can be faster by using a GPU. As for the accuracy, we split the dataset into training and testing sets with a ratio of 9:1 and calculated the error of each testing record. The mean absolute error is $1.04m/s$. This speed error is acceptable considering the high shuttle speed (*i.e.*, $10m/s \sim 80m/s$) produced by the top player. Figure 11b further presents the distribution of relative errors between testing outputs and their ground truths in different speeds, indicating that our model can achieve a low error rate ($< 5\%$) for various stroke speeds.

Fig. 11. Left: The error per epoch for the training and testing sets. Right: The relative error between testing outputs and ground truths with different stroke speeds.

5 Implementation

ShuttleSpace is built on HTC VIVE Pro VR system [1] that includes a VR headset, a pair of handheld controllers, and other accessories. The VR headset provides a stereoscopic display with a 110° FOV, enabling the content to be presented in a real 3D form. To track the user's location and body motions, we utilize a SteamVR system so that the user can move as if he/she were in a real badminton court. These features ensure an immersive first-person experience. The controllers we used can record instantaneous velocity and position, which are critical for simulating a stroke in Sec. 4.4. Besides the hardware, our system is implemented based on Unity with C# and HLSL that leverage GPUs to ensure the frame rate and reduce the VR sickness. We use XChart package to create the visual designs in 4.3. With a Nvidia 1080 GTX graphics card and an Intel Core i7 CPU, our system can achieve 50 frames per second in the case studies and expert interview.

6 Evaluation

We evaluate our system by inviting four domain experts to conduct case studies on a real-world dataset. We first present two insights founded

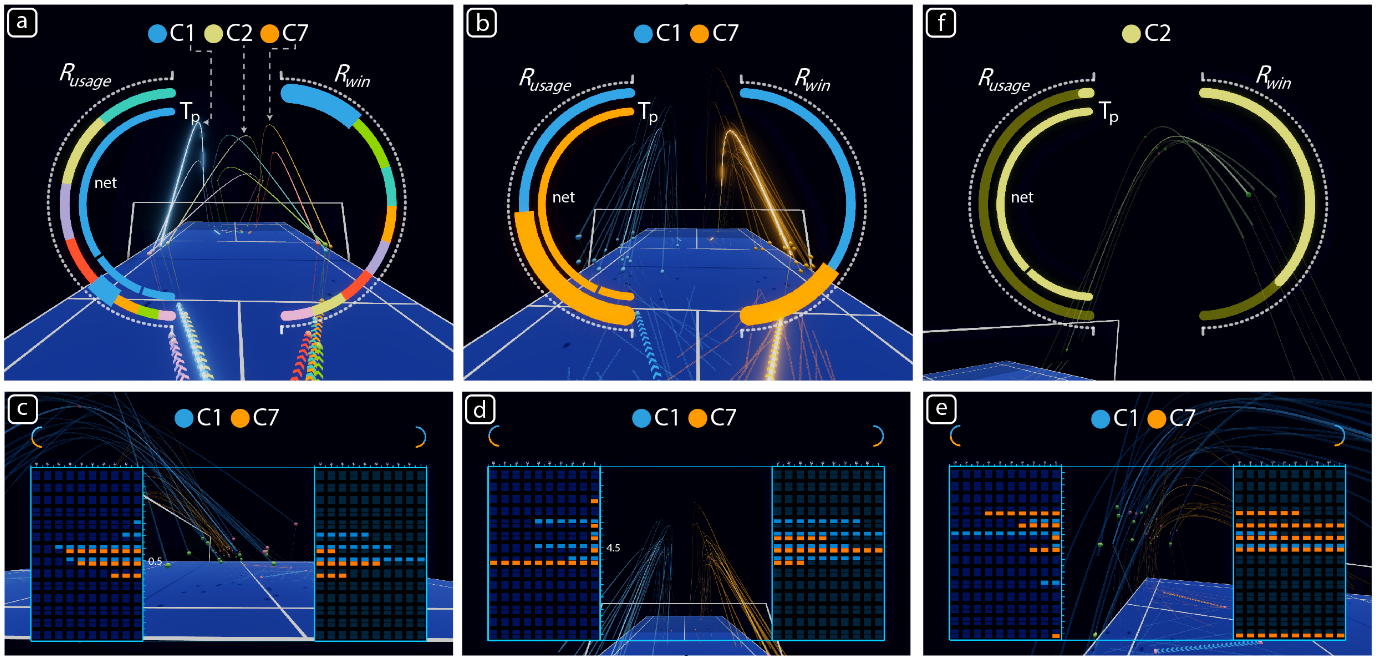


Fig. 12. Insight I shows that why C1 is similar to C7 but has a higher R_{win}. a) C1, which represents the trajectories of *defensive lob*, has the highest R_{win}. The most frequently used previous technique (T_P) of C1 is *net shot*. C7 is very similar to C1 but has a low R_{win}. b) A comparison between C1 and C7. The most frequently used previous technique of C7 is also *net shot*. c) The P_{start} in C1 are higher than those in C7. d) The $P_{highest}$ in C1 are also higher than those in C7. e) The P_{end} in C1 are lower than those in C7. f) The pattern of using high *defensive lob* to defuse a *net shot* also exists in C2.

by the experts and their exploration processes. We then summarize the feedback from the post-study interview. We provide an additional insight in the supplemental materials.

6.1 Experiment Settings

Our main experiment settings are as follows:

Dataset. The dataset comprises nine men's singles matches from the *Badminton World Federation World Tour* 2018 season, involving 6 of the top 10 men's singles players in the world in 2018. The dataset contains 3812 strokes in total. In the study, all the experts focused on the *lob* strokes, which occupy *80%* of the records. Our system clustered these *lob* strokes into eight categories. Please note that the dataset only contains the key points of $T_{shuttle}$ and T_{player} rather than real trajectories. We reconstructed the trajectories using the method mentioned in Sect. 3.2. An improved case study can be conducted once datasets of real trajectories are available.

Participants. Four badminton experts (referred to as E1-E4) participated in our case studies. One of the experts is a professor of badminton sports who has worked for one of the top national badminton teams over five years. He also attended the two-hour weekly meetings during the collaboration. The three other experts, who had never been presented the system before, are majoring in physical education with rich experiences in badminton analysis and training. All the experts had not explored the dataset used in the evaluation before our study.

Apparatus. The studies were conducted in a $7m \times 7m \times 3m$ room that covers the space of a half-court. The size of the simulated court in our system was similar to a real standard badminton court. We allowed the expert to switch the half-court by pushing a button. We used a HTC VIVE Pro headset equipped with a wireless adaptor to ensure the experts can freely move in the room.

Procedure. We first introduced the VR platform and our system to the experts before exploring the data. We then helped the experts in wearing the devices and adjusted the VR headset for each expert to ensure comfortablility. The experts were encouraged to freely explore the system and ask questions regarding the system voluntarily. We began the studies when the experts were confident about using the system. During the studies, The experts shared their real-time screen in the VR with us. The experts were allowed to ask questions regarding the system and take a rest if needed. The exploration lasted 30 minutes and would then be completed based on the experts' preference. Finally, we conducted a post-task interview to gather feedback.

6.2 Cases and Insights

Insight I: Using a high *defensive lob* to defuse a *net shot*.

This case conducted by E1 shows how the expert found an interesting *defensive lob* pattern that can cope with the threat of the opponent's *net shot*. There are 945 stroke records in this case. Through *Donut View* (Fig. 12a), the expert quickly found that category1 (C1), a kind of *defensive lob*, has a significant higher R_{win} than others. By walking in the simulated court, he noticed that category7 (C7), also a kind of *defensive lob*, is very similar to C1 but has a lower R_{win} (Fig. 12a). To figure out the reasons behind such R_{win} difference, the expert decided to compare these two categories. Thus, he selected these two categories by using *VirtualStroke*. ShuttleSpace then unfolded the trajectories in these two categories (Fig. 12b).

Step1: Checking the previous technique. Based on the domain knowledge, the expert knew that a stroke is mainly affected by the technique used by the opponent in the previous stroke. Thus, he first checked the technique of the previous strokes in C1 and C7, respectively. According to the inner donut chart in *Donut View* (Fig. 12a and b), he identified that both the previous techniques of C1 and C7 are dominated by *net shot*, which means the R_{win} difference between C1 and C7 is not caused by the previous technique. Conclusion: Both C1 and C7 are mainly used to cope with *net shot*.

Step2: Comparing the trajectory key points. Next, the expert filtered the strokes and focused on those whose previous techniques are *net shot*. He came to the stroke area and observed the P_{start} of the shuttle trajectories, *i.e.*, the shot points. As shown in Fig. 12c, the height of P_{start} in C1 is higher than those in C7. Most of the P_{start} in C1 are higher than 0.5m. He knew that the higher the P_{start} is, the greater is the flexibility for the player to adjust the stroke direction for a high-quality return. Then he raised his head to check $P_{highest}$ of the trajectories. The distribution in *Grid View* presented that most of $P_{highest}$ in C1 are higher than those in C7 (Fig. 12d). Specifically, a majority of $P_{highest}$ in C1 are higher than 4.5m. The expert explained that a higher trajectory indicates a slower flying speed of the shuttle, which restricts the opponent from intercepting the shuttle with a smash. Finally, he went to the opponent's half-court to see P_{end} of the shuttle trajectories, *i.e.*, the opponent's shot point. He opened *Grid View*, which showed that most of the P_{end} in C1 are lower than those in C7 (Fig. 12e). Moreover, he discovered that the moving distances of the opponent in C1 are longer than those in C7. These findings reminded him that a shuttle trajectory that has a low P_{end} and forces the opponent to move longer can cause a passive situation, in which the opponent experiences greater difficulty in performing a high-quality return. The expert thought that this is the reason why C1 has a higher R_{win} than C7. Considering these observations, he reached the following *Conclusion:* A *defensive lob* with high P_{start} ($>$ 0.5m) and $P_{highest}$ ($>$ 4.5m) can increase the opponent's pressure and the winning rate.

Step3: Verifying the conclusions. Finally, the expert wanted to verify whether his conclusions were held in other categories of strokes. Thus, he selected category2 (C2) which was also a kind of *defensive lob* (Fig. 12a). He used *VirtualStroke* to query the trajectories with a P_{start} $>$ 0.5m and $P_{highest}$ $>$ 4.5m. ShuttleSpace retrieved the targeted strokes immediately and presented their data in Fig. 12f. The expert found out that these strokes in C2 also had a high R_{win} and forced the opponent to return the shuttle in a low position after long-distance movement. These findings confirmed his conclusions. Thus, he reached this final *Conclusion:* if the opponent performed a *net shot*, then the player should use a *defensive lob* to return the shuttle at a position higher than 0.5m and ensure that its $P_{highest}$ is higher than 4.5m.

Insight II: Beat Kento Momota by using a net shot to create *smash* opportunities.

In this case, E4 explored the *lob* strokes of Kento Momota, who is famous for his unpredictable style of play, to find his weakness. There are 227 stroke records in this case.

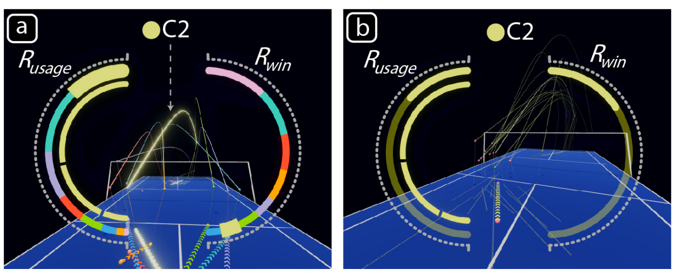


Fig. 13. Insight II: The stroke data of Kento Momota. a) The overview of Momota's *lob* strokes. C2 is his most frequently used strokes but has a low winning rate. b) When performing a C2 stroke, Momota usually moves from the mid-right side to the front-left side of the court.

Step1: Exploring the overall stroking patterns of Momota. The expert was familiar with Momota and had spent a long time to study his plays. From Fig. 13a, category2 (C2) is the most frequently used strokes of Momota. However, the expert was surprised that C2 has a low R_{win}, as Momota, a left-hand player, should have advantage at the left side of the court. The expert thought this could be a weakness of Momota and develop a winning strategy to beat him—if we can force Momota to perform a C2 stroke, we will have more chances to win this rally. Thus, he selected C2 for a detailed investigation.

Step2: Checking the trajectory key points. The expert first wanted to identify in what situation Momota will perform a stroke of C2. Following Momota's movements, the expert found out that in most cases of C2, Momota stands (*i.e.*, P_{start}) in the mid-right side of the court and then moves to the front-left side of the court to stroke the shuttle (Fig. 13b). From the previous techniques, the expert also identified that Momota mainly perform C2 to handle *spin net shot* and *cross-court net shot*. Next, by observing the shot points (*i.e.*, P_{start} of the $T_{shuttle}$) the expert then noticed that Momota tends to stroke the shuttle at a position that is low and near the net. Through *Grid View* (Fig. 14a, the expert knew that the shot positions are specifically lower than 0.6m. Based on these findings, the expert drew a *Conclusion:* when Momota is at the mid-right side of the court, use *spin net shot* or *cross-court net shot* to hit the shuttle to a position that is at the front-left side of the court and lower than 0.6m.

Step3: Exploring how to prepare for Momota's C2. Finally, the expert further wanted to investigate how to prepare for Momota's strokes of C2. Therefore he switched to the half-court of Momota's opponent and explored the P_{end} of the shuttle trajectories. The expert discovered that most of these points are close to the back-right side of the court (Fig. 14b). Moreover, according to *Grid View*, Momota are more likely to lose the rally if the opponent returned the shuttle when it is higher than 2.5m (Fig. 14c). By exploring the techniques used in the next strokes, the expert understood that the opponents primarily return Momota's C2 using *smash*. With these evidences, the expert came to a *Conclusion:* after forcing Momota to perform a stroke of C2, the player should move back to the back-right side of the court and prepare to *smash* the shuttle at a place that is higher than 2.5m.

6.3 Interview Feedback

We summarize and report the feedback gathered from the expert interview session and the observations during the study.

Immersive visualization for 3D and 2D data—natural and suitable. We were interested in the comments of experts regarding using immersive visualization to present the 3D and 2D data. All the experts believed that using immersive 3D to present the trajectory data is natural and better than using 2D visualizations on traditional desktop computers. The main reason is that "*if presenting the 3D data in 2D, I will need to imagine the 3D scene in my brain [sic].*" (E1) We also discussed about the differences between 3D visualizations in immersive environments and those on traditional desktop platforms. Three of the experts (E1, E2, E4) preferred the immersive environment because "*the field of view is larger...[sic]*" and "*the stereoscopic display is made for 3D...[sic]*" By contrast, E3 preferred traditional desktop platforms because "*wearing the VR headset is easy to be tired [sic].*" Considering the combined 2D and 3D visualizations using the peripheral vision, the experts thought that this method is appropriate and effective. E2

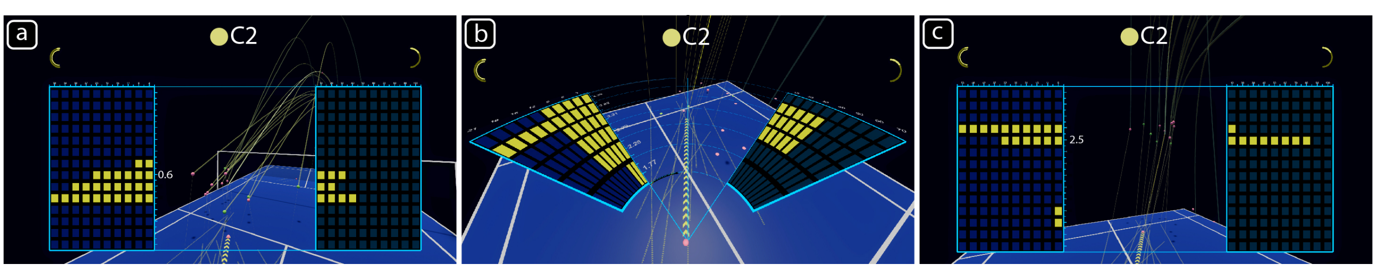


Fig. 14. Insight II: Detailed investigations of Momota's C2. a) Momota usually performs a C2 stroke when the shuttle is at the front-left side of the court and lower than 0.6m. b) Momota's C2 hit the shuttle to the back-right side of the court. c) Returning Momota's C2 at a place that is higher than 2.5m leads to a high winning rate.

commended that both *Donut View* and *Grid View* is *"convenient to obtain information [sic]"* because they *"are always within the field of view [sic]"* and *"never occlude what I am looking at [sic]."*

Immersive first-person view—experience, besides analysis. Overall, the experts appreciated the immersive experience and thought that the system supports situation awareness to facilitate the combination of their domain knowledge and the environmental information. E1 said that "*in the system the trajectories are not just numbers but something real [sic].*" E3 thought that compared with traditional desktop platforms, the immersive environment "*provides more information [sic]*", since "*...when I stand at there, I know what is happening, I know how high I should jump, and how fast I should run to stroke the shuttle... [sic]*" E4 agreed that the immersive environment not only provides the data for analysis but also the experience on the court. However, the four experts also suggested that we should provide a third-person omniscient mode by scaling down the entire scene (*e.g.*, to 1: 10) to obtain an overview of the data before entering the first-person view (wherein the model size is 1:1). We consider this suggestion as an important future improvement.

Metaphorical interaction—learn from the selection. All the experts spoken highly of our *VirtualStroke* for trajectory selections. As commented by E4, the interaction "*is easy to learn and easy to use*" and "*allows selecting the trajectories I wanted [sic].*" Although we observed that the system incorrectly inferred the selection of E2 several times, E2 still thought that "*the interaction design is wonderful [sic]*" and the errors were acceptable because "*the system and the underlying algorithm can be improved in the future [sic].*" Particularly, E4 indicated that *VirtualStroke* can further enhance the user's understanding of the selected trajectories because "*the stroke action recalls my muscle memory...I can learn some characteristics of the trajectories from the selection action itself [sic].*" Nevertheless, the experts also recognized that using *VirtualStroke* to select the trajectories that require high level stroke skills, *e.g.*, *around the head smash*, is occasionally difficult. Although the targeted users of our system, *i.e.*, domain experts, are familiar with these stroke skills, we agree that future study should be conducted to lower the barrier to select trajectories of high level skills.

Suggestions. The experts also identified some limitations of our system and provided constructive suggestions. Most of the limitations proposed by the experts during the study were related to tool maturity. For example, the legibility of text labels and legends can be improved; the color theme of the system should be customizable. Our system also involves certain inherent limitations. First, the VR headset is bulky and thus increases the physical workload. The experts generally needed to take a break every 15 minutes during the studies. Second, the VR environment separates the user from the real world, causing hesitation from the user to walk around before getting used to the environment. We observed that at the beginning of the studies, the experts carefully attempted to move their feet to avoid falling to the floor. They became confident to move in the simulated court when they got used to the immersive environment. After a discussion with the experts, we proposed to use some reference points to relate the virtuality and reality. For example, we can put a chair in the real room and use a similar virtual chair in the virtual court to indicate the position of the user in relation to the real room. Third, the controllers cannot simulate the haptic feedback of stroking a shuttle, thus requiring the experts to spend a certain time to adapt.

7 Discussion

Significance—from flat screen to immersive display. Sports generate a huge amount of data, which is mainly 3D and spatial by nature. However, prior visual analytics systems for sports data are mainly developed on traditional 2D screens, which require the analysts to imagine the 3D scenes in their mind. The low cost immersive devices (*e.g.*, VR and AR) introduce opportunities to engage with sports data in a direct and intuitive manner. We explore this direction and leverage the VR devices to enable embodied data analytics. Our case studies demonstrate that the domain experts could successfully use our system to analyze real-world datasets and discover useful insights. However, we consider the immersive platform as a complement to the traditional desktop platform, rather then a substitution, despite the envisioned high potential of immersive analytics for sports data. Future sports analytics systems may be designed to include "immersive" and "desktop" modes.

Generalizability—from badminton to other sports. Though our system is intended for analyzing badminton data analysis, its main design can be generalized to other sports with certain adaptations. For example, our system can be naturally adapted to racket sports, such as tennis, basque pelota, and table tennis. Moreover, our two key designs, namely, leveraging the peripheral vision to combine 2D and 3D visualizations and the VR controllers to support metaphorical interactions, can be shifted and adopted in other immersive analytics systems.

Potentiality—from offline VR to online AR. Currently, our system only supports analysis in an offline manner; that is, the data is collected beforehand. However, in practices, the coaches must decide in real-time for coaching, and the players must occasionally obtain the feedback immediately during training. Realizing these requirements can be difficult for VR devices, but AR platforms can provide such kind of in-situ interactive visual analysis. From a technical aspect, AR provides a super-set of functions than VR, supporting virtual content embedding in the real world. Though AR increased opportunities for sports analysis, it also involves additional challenges than VR, such as online streaming data analysis [48] and designing visualizations on the real-world canvas. Furthermore, different motion capture techniques in AR may require more complex mapping models [21, 49]. Lin et al. [20] have recently summarized and identified the unique challenges and opportunities of employing AR for sports analysis. We hope the obtained findings in this study can provide a basis for further exploration towards this direction.

Study Limitations. Similar to other studies of sports analytics [45, 46], the sample size of our case studies is small because the access to experts is naturally limited. In addition, the trajectory data used in the case studies is not real but reconstructed. Further evaluation is suggested once complete tracking data is available due to the challenges posed by the complexity of trajectory data [22]. Besides, our system only focuses on the spatial aspect of the stroke data and excludes the temporal dimension. We only allow the user to check the distribution of techniques used in the previous or next stroke but disregard further investigations of the stroke sequence. We consider this as an important future improvement. Finally, the design of our system is not meant to handle large-scale cases (*e.g.*, tens of thousands of strokes or dozens of stroke categories), which are rare in badminton analysis according to our domain experts.

8 Conclusion

In this work, we propose ShuttleSpace, an immersive visual analytics system for analyzing trajectory data in badminton from a first-person perspective. We collaborate closely with four domain experts, who have worked for a top national badminton team in the world over 5 years, to identify the system requirements and propose the design goals. Our system features *Donut View* and *Grid View*, which leverage the near-peripheral vision to seamlessly combine 2D and 3D visualizations from a first-person perspective, and *VirtualStroke* that uses the VR controller to support natural selections of 3D trajectories. To evaluate our system, we invite domain experts to conduct case studies on a real-world dataset using our system. We present two useful insights discovered by the experts and their exploration processes. We also summarize and report our observations during the study and the feedback from the post-study interview. The evaluation and expert feedback confirm the effectiveness and usefulness of our system.

Acknowledgments

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